Overreaction to growth opportunities: an explanation of the asset growth anomaly

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Abstract

The negative relation between asset growth and subsequent stock returns is known as the asset growth anomaly. We propose that overreaction to growth opportunities is the source of the asset growth anomaly. This suggests that growth firms as opposed to mature firms, and firms with longer series of asset growth should experience a stronger asset growth anomaly. Our evidence supports these predictions.

Keywords: asset growth, anomaly, overreaction, growth opportunities, US market

GEL codes: G1, M4

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1. Introduction

The efficient market hypothesis has faced a long line of challenges from persistent anomalies (see Schwert, 2003, for a survey). The asset growth anomaly, where subsequent returns are negatively related to asset growth, is one of the latest to be investigated. Cooper *et al.* (2008) and Fama and French (2008) show that firms have lower subsequent returns when they expand their assets and, conversely, higher subsequent returns when their assets contract[1]; since the Fama–French 3-factor model cannot explain the returns of portfolios sorted by asset growth, this negative relationship between asset growth and future stock returns at the cross-sectional level is referred to as the asset growth anomaly.

While both rational and mispricing explanations of the asset growth anomaly have been proposed, much of the recent evidence in the literature has been focused on rational explanations via *q*-theory. The latter is largely inconclusive[2], and mispricing as an explanation has received considerably less attention. Given the mixed evidence to date, the purpose of this paper is to extend our understanding of the drivers of this phenomenon by focusing on investor overreaction as an explanation of the asset growth anomaly. Such a conjecture has its origin in the anomaly literature (Cooper *et al.*, 2008). Extending their finding, if the asset growth anomaly is driven by investor overreaction to asset growth

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1 For events associated with expansion, Loughran and Ritter (1995) show that firms with equity issuance earn lower stock returns. For events associated with contraction, Lakonishok and Vermaelen (1990) show that firms with share repurchase earn higher returns.

2 The rational explanation of the asset growth anomaly relies on the *q*-theory model, which studies the investment–return relationship from a production-based asset pricing or firm optimal investment standpoint (e.g., Cochrane, 1991, 1996; Chen and Zhang, 2010; Li *et al.*, 2009; Li and Zhang, 2010). The basic argument is that firms with low discount rates (expected returns) have high net present values and high investment, whereas firms with high discount rates have low net present values and low investment. Li and Zhang (2010) show that limits-to-arbitrage dominates *q*-theory in explaining the asset growth anomaly. Watanabe *et al.* (2013) favour the optimal investment explanation by using global stock markets; they find that the asset growth anomaly is stronger in more advanced markets where stocks are more efficiently priced. Finally, Lam and Wei (2011) present evidence to support both limits to arbitrage and *q*-theory.

news, it follows that growth firms will be more likely to experience such an anomaly, as they should generate more growth news to be extrapolated by investors.

We therefore develop two hypotheses concerning investor reaction to asset growth. First, if overreaction to growth explains the anomaly, then growth firms should show a stronger asset growth anomaly than mature firms[3]. Second, the behavioural bias of representativeness suggests that investors overreact more to a *series* of events, and therefore, if overreaction is the explanation, then firms experiencing a longer series of high (low) asset growth should experience lower (higher) subsequent returns; thus the anomaly would be stronger for firms experiencing a sequence in their growth pattern[4]. It is often argued that investors extrapolate a sequence of same-signed news, which results in an overreaction to the information (see, for example, the theoretical model of Barberis *et al.*, 1998)[5].

To test the first hypothesis we employ three growth-type proxies: retained earnings scaled by firm total assets, the dividend-to-income ratio, and cash flow scaled by firm total assets. Growth firms tend to have lower retained earnings, dividends and cash flow than mature firms (see Anthony and Ramesh, 1992; DeAngelo *et al.*, 2006; Dickinson, 2011). Using US data from 1963 to 2011, we show, by comparing the hedged returns of asset growth-sorted portfolios for growth and mature firms, that growth firms demonstrate a stronger asset growth anomaly. Sorting on asset growth within growth type yields an

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[3] Firm life cycle has been shown to be a useful dimension in understanding the cross-sectional variation of corporate finance decisions and accounting ratios. For example, Hirsch and Walz (2011) show that firms in different life-cycle patterns make different financing decisions and that these decisions interact with future growth and development decisions. Hribar and Yehuda (2015) study the mispricing of accrual and cash flow information by the stock market in different firm life-cycle stages.

[4] According to Barberis *et al.* (1998), after a trend of good or bad information, representativeness causes investors to overreact to information and push the price too high. Hong and Stein (1999) argue that momentum traders make decisions conditional on past price change; that is, they push stock prices higher (lower) when there is an up (down) trend.

[5] Alti and Tetlock (2014) use a structure model approach to study the influence of behavioural biases on asset prices. They also identify over-extrapolative belief as the main cause of mispricing.

annualized return difference between growth and mature firms of 20%, 18% and 13% respectively for the three proxies of growth type – retained earnings, dividend-to-income ratio and cash flow. The Fama–MacBeth regression results provide further support: for example, they show that the slope of asset growth for growth (mature) firms is -0.0124 (-0.0042), when the growth-type proxy is retained earnings.

To test the second hypothesis, we construct four asset growth sequence portfolios each for high- and low-growth firms. For the high-growth sequence portfolios, we construct four portfolios of firms that experience asset growth in the top two asset growth deciles for one year or consecutively for two, three, or four years respectively. The four low-growth sequence portfolios are similarly constructed. We find, by comparing the slope of each growth sequence portfolio, that as the asset growth sequence increases, the asset growth anomaly becomes stronger. This is especially the case for high-growth sequences. In addition to univariate tests, we further examine the interaction between growth type and asset growth, and between growth sequence and asset growth, after controlling for the two prominent explanations of the asset growth anomaly – limits to arbitrage and *q*-theory with investment frictions. We use five limits-to-arbitrage proxies (idiosyncratic volatility, bid–ask spread, analyst coverage, analyst forecast dispersion, dollar trading volume) and two investment friction proxies (firm age, firm total assets). In the majority of cases, the evidence suggests that growth firms and longer growth sequences produce a stronger asset growth anomaly. The evidence of investor overreaction only to positive sequences, not to negative sequences, provides further support to the argument that it is growth, specifically, that investors overreact to.

In summary, we find evidence to support the overreaction explanation of the asset growth anomaly, and our paper contributes to the literature in the following ways. Complementing Cooper *et al.* (2008), we provide evidence that a firm's growth type affects the reaction of investors to news of asset growth. More importantly, we also present new evidence to support the suggestion that overreaction is a key driver of the asset growth anomaly: we show that both firm growth type and growth sequence are able to capture investor overreaction and afford additional explanatory power over the asset growth anomaly[6].

The prior literature on mispricing explanations mainly tests whether firms with different limits-to-arbitrage levels show different degrees of the asset growth anomaly (Lam and Wei, 2011; Watanabe *et al.*, 2013). However, the limits-to-arbitrage approach only studies the constraints on correction of the initial mispricing; it does not explicitly analyse whether the mispricing is due to over- or underreaction. We contribute to this line of literature by studying overreaction as the source of mispricing.

However, Cooper *et al.* (2008) do provide some evidence on testing overreaction to past earnings: they show that investors are indeed surprised by the subsequent bad (good) earnings for high (low) asset growth firms. Although such evidence supports the notion that it is expectation errors that cause mispricing (Lakonishok *et al.*, 1994), the sources of these errors are not explicitly identified. We show that it is investor overreaction to growth opportunities that drives expectation errors and causes the asset growth anomaly.

We contribute to the literature by testing the overreaction to growth in a sequential setup. Our unique research design enables us to show that there are elements of the asset growth anomaly that can be explained by investor overreaction. The explanatory power of the overreaction explanation persists even when we control for limits to arbitrage and *q*-

[6] Hribar and Yehuda (2015) also employ the firm life-cycle concept to study the mispricing of accrual and cash flow information by the stock market. They show that both total accruals and free cash flows are mispriced to the highest degree in the growth stage. However, the focus of their study was to highlight the different information contents of accruals and cash flow in different firm life cycles; there was little discussion on the reason for the difference in the strength of the anomaly in different life cycles.

theory, which means that both firm growth type and growth sequence are able to reflect investor overreaction to asset growth information.

The remainder of the paper is organized as follows. Section 2 reviews the extant asset growth anomaly literature and constructs our hypotheses. Section 3 describes the data and variables used in this study. Section 4 presents empirical results for firm growth type and the asset growth anomaly, while Section 5 presents results for the asset growth sequence portfolios and the representativeness explanation. Section 6 details robustness testing and further evidence. Section 7 concludes.

2. Related literature and hypothesis development

In Section 2.1 we review briefly the literatures on mispricing with limits to arbitrage and *q*-theory with investment frictions. In Section 2.2 we develop our two hypotheses positing overreaction to growth as an explanation of the asset growth anomaly.

2.1 Mispricing with limits to arbitrage and q*-theory with investment frictions*

Two branches of explanation are proposed in the literature: risk-based (rational) and mispricing (behavioural). Regarding the risk-based explanation, upon discovery of the asset growth anomaly Cooper *et al.* (2008) test this explanation and show that standard risk factor analysis such as by means of 3-factor models and the conditional CAPM, using a standard set of macroeconomic variables, cannot explain the effect. They also show that the asset growth effect is not consistent with the implication of the theoretical papers that expected returns should systematically decline in response to increasing investment. They therefore reject the explanation of time-varying risk induced by changes in the mix of firm growth options and assets in place. Overall, Cooper *et al.* (2008) dismiss the rational risk-based explanation of the asset growth anomaly.

More recent searches for a rational explanation shift the perspective from investor to firm. *Q*-theory suggests that firms invest when the discount rate (expected return) is lower, because a lower discount rate leads to a higher net present value and, consequently, a negative investment–return relation is observed (e.g., Cochrane, 1991, 1996). However, such a prediction is difficult to test empirically since managerial expectations of a discount rate are unobservable and it requires the strong assumption of market efficiency to make connections between managerial expected discount rates and subsequent realized stock returns. As a way forward, Li and Zhang (2010) construct an optimal investment model by incorporating investment frictions to *q*-theory. Firms with high investment frictions produce higher investment costs and are therefore not as sensitive to changes in the discount rate; that is, only large decreases in the discount rate can induce firms with high frictions to invest. If *q*-theory accounts for the asset growth anomaly, it would predict that firms with higher investment frictions will show a stronger asset growth anomaly. *Q*-theory with investment frictions has received some support in the literature; for example, Chen and Zhang (2010) develop a 3-factor model based on *q*-theory and find supportive evidence.

A parallel development in the literature is the mispricing explanation of the asset growth anomaly. Cooper *et al.* (2008) argue that the asset growth anomaly reflects investor overreaction to firm growth (contraction). They find that firms which grow (contract) tend to be firms with future negative (positive) profitability shocks with respect to performance in the sorting year. Furthermore, they show that subsequent earnings announcements for low-growth firms are associated with positive abnormal returns and *vice versa*. These results are consistent with the La Porta *et al.* (1997) expectation errors mispricing story.

Further developments in this line of research focus more on the conditions for mispricing to persist after it occurs; namely, limits to arbitrage. Both Li and Zhang (2010) and Lam and Wei (2011) propose that if mispricing leads to the asset growth anomaly, then firms with high limits to arbitrage should exhibit a stronger asset growth anomaly than those with low limits to arbitrage. The reason is that the anomaly cannot be traded away quickly and should last for longer periods when there are high limits to arbitrage such as high transaction costs, high stock volatility and/or little information about the firm. It is important to note that these studies do not directly examine the underlying cause of the mispricing. There is an implicit assumption that mispricing occurs in the market and arbitrage fails to fully correct it.

Lipson *et al.*, (2011) find that firms with high transaction costs have a stronger asset growth anomaly, which is consistent with the mispricing with limits-to-arbitrage explanation. Li and Zhang (2010) and Lam and Wei (2011) compare the explanations of mispricing with limits to arbitrage and *q*-theory with investment frictions. Li and Zhang (2010) find that the explanatory power of mispricing with limits to arbitrage is stronger than that of *q*-theory. With a more comprehensive set of proxies for limits to arbitrage and investment frictions, Lam and Wei (2011) show that the two explanations have similar explanatory power in terms of the asset growth anomaly; they also consider the high correlation between the limits-to-arbitrage and investment friction proxies as a key issue in trying to distinguish between the two explanations. More recently, in an attempt to address this issue, Titman *et al.* (2013) and Watanabe *et al.* (2013) undertake cross-country studies and find a stronger asset growth anomaly in more developed stock markets than less developed markets, which is consistent with dynamically optimal investment; that is, they find support for *q*-theory.

In summary, while the literature demonstrates support for both *q*-theory with investment frictions and mispricing with limits to arbitrage to explain the asset growth anomaly, recent studies have leaned more towards the *q*-theory explanation. Mispricing as an explanation of the phenomenon has received less attention since Cooper *et al.*'s (2008) early analysis. Importantly, recent studies on the mispricing explanation only focus on the conditions for the subsequent persistence of mispricing rather than the cause of the initial pricing. Our study aims to fill this void.

2.2 Testable hypotheses

In this study, we investigate how investors react to firm growth information and examine how far any overreaction can be related to the representativeness heuristic.

Lakonishok *et al.* (1994) claim that investors extrapolate firm performance too far into the future and therefore push the price too high or low, causing a subsequent reversal. Their argument implies that investors overreact to a firm's prospects. In essence, investors display unrealistic views about a firm's prospects and are unable to forecast (e.g., Weinstein, 1980; Buehler *et al.*, 1994).

Growth firms are usually characterized as relatively young and small, and have less information available but more growth opportunities or better growth prospects. In contrast, mature firms are characterized as having long histories, large size and more information available but less growth opportunity. Therefore, investors should overreact more to growth firms because of their greater growth opportunities in comparison to mature firms. These arguments lead to our first hypothesis.

H1. *Growth firms should exhibit a stronger asset growth anomaly (negative relation between asset growth and stock returns) than mature firms, because of overreaction to greater growth opportunities.*

Barberis *et al.* (1998) argue that investors tend to confirm the sequence when they witness one asset growth surprise followed by another. This is consistent with representativeness[7], and implies that the longer the asset growth sequence, the stronger the asset growth anomaly. Specifically, when investors see a consecutive high asset growth series, they believe that the sequence will continue and they push the price to a high level – and to an even higher level when the series is longer. Afterwards, when investors recognize the reality

[7] Tversky and Kahneman (1974) show representativeness as a behavioural heuristic; that is, people determine probability by using a sample that they think reflects the distribution of the population. Such a process results in the bias of over-generalizing recent observations.

and correct their valuation, the stock prices reverse. As a result, a negative relation between asset growth and subsequent returns should be observed[8]. If this is the case, the findings will tend to support overreaction as the explanation of the asset growth anomaly; furthermore, the representativeness heuristic will be the underlying driver of this overreaction. Hence, we develop our second hypothesis.

H2. *Firms with longer asset growth sequences should exhibit a stronger asset growth anomaly (negative relation between asset growth and stock returns), ceteris paribus, than firms with shorter asset growth sequences, because of the representativeness bias.*

3. Data and variables

3.1 Sample selection

We use US data including NYSE, AMEX and Nasdaq from 1963 to 2011 based on the CRSP and Compustat datasets. Monthly stock returns are from CRSP and yearly financial reporting variables are from Compustat. We exclude financial firms with 4-digit SIC codes between 6000 and 6999[9]. For analyst data, that is, the number of analysts covering a firm and the dispersion in analyst forecasts, we start from 1977 due to the availability of data. To avoid the problems of survivorship or selection bias, we follow Fama and French (1993) and Cooper *et al.* (2008) in retaining only those firms with at least two years of Compustat data[10]. There remain 172,732 firm–year observations after following the above sample selection procedure. For some portfolio formations, we require four years of data

[8] In general, overreaction is defined as investors overreacting to past asset growth information. This works in both high- and low-growth firms. In other words, when investors observe a series of high (low) growth they will extrapolate and expect continued high (low) growth in the future. When this error is corrected, we observer a reversal in returns for both high- and low-growth firms.

[9] Fama and French (2008), Cooper *et al.* (2008) and Lam and Wei (2011) do not include financial firms in their` sample when investigating the asset growth anomaly.

[10] Banz and Breen (1986) and Lam and Wei (2011) also set this requirement when selecting their samples, in order to minimize the selection bias.

availability prior to the formation date. For our Fama–MacBeth regressions, we update returns monthly and asset growth or other financial variables on a yearly basis.

3.2 Asset growth measurement

Following Cooper *et al.* (2008) we use the percentage change of a firm's assets between the current and previous year as the measure of firm asset growth (*AG*). That is, $AG = TA_{t-1}/TA_{t-2} - 1$. Lipson *et al.* (2011) compare different definitions of asset growth and show that there is little effect on the asset growth anomaly. (The construction of asset growth and the following proxies are detailed in the appendix.)

3.3 Proxies of growth type

We use three measures to proxy the growth stage of a firm: retained earnings scaled by total assets (*RE*), dividends scaled by income (*DIV*) and cash flow scaled by total assets (*CF*).

The first growth-type proxy is retained earnings scaled by total assets (*RE*). DeAngelo *et al.* (2006) show evidence that retained earnings as a proportion of total assets is a good proxy of growth type – that is, firms with high *RE* are in the maturity stage while firms with low *RE* are more likely to be growth firms. They also find a strong positive relation between *RE* and dividends: specifically, high-*RE* firms have more motivation to distribute dividends because they have less investment opportunity and enough capacity to self-finance; in contrast, low-*RE* firms are not likely to be dividend payers because they face abundant investment opportunities. This leads to our second proxy.

The second growth-type proxy is dividends scaled by income (*DIV*), which is used in previous literature (e.g., Anthony and Ramesh, 1992; Bulan *et al.*, 2007). Following Anthony and Ramesh (1992), we classify high-*DIV* firms as mature firms and low-*DIV* firms as growth firms. DeAngelo *et al.* (2010) show that these dividend groups are reasonable proxies for life-cycle stage.

The third growth-type proxy is cash flow scaled by total assets (*CF*). Growth firms have a large investment opportunity set and invest more than the cash they can generate, so they are characterized by low cash flows (e.g., Dickinson, 2011). In contrast, mature firms have the ability to generate high cash flows.

3.4 Proxies of investment frictions

We use two proxies for investment frictions. The first is firm age (*AGE*). Younger firms have less information available in the market because they have shorter histories (e.g., Barry and Brown, 1985; Zhang, 2006). Without sufficient information, younger firms face greater financing constraints.

The other proxy for investment frictions is firm size measured by total assets (*TA*). The market usually has less information about small firms, which are not attractive to investors and so lack attention. Both Li and Zhang (2010) and Lam and Wei (2011) also use asset size as a proxy for investment frictions.

3.5 Proxies of limits to arbitrage

We use five proxies for limits to arbitrage: idiosyncratic volatility (*IVOL*), bid–ask spread (*BAS*), analyst coverage (*COV*), analyst forecast dispersion (*DISP*) and dollar trading volume (*DVOL*).

The first proxy of limits to arbitrage is idiosyncratic volatility (*IVOL*). Unlike total return volatility, idiosyncratic volatility measures the firm-specific or unsystematic arbitrage risk in terms of firm-specific information (e.g., Pontiff, 1996; Wurgler and Zhuravskaya, 2002; Ali *et al.*, 2003).

The second proxy of limits to arbitrage is the bid–ask spread (*BAS*), with a larger bid–ask spread suggesting higher transaction costs (e.g., Lam and Wei, 2011). These would set constraints on arbitrage behaviour, and therefore a larger bid–ask spread means higher limits to arbitrage.

The third proxy of limits to arbitrage, analyst coverage (*COV*), measures the number of financial analysts covering the firm, on the assumption that the greater the number of analysts, the more the investors will be able to access information about the firm, and so make more reliable decisions. Hong *et al.* (2000) argue that lower analyst coverage means higher information uncertainty. Lam and Wei (2011) find that the asset growth anomaly is stronger for firms with high limits-to-arbitrage, and they too use analyst coverage as a limits-to-arbitrage proxy.

The fourth proxy of limits to arbitrage, analyst forecast dispersion (*DISP*), reflects the disagreement in analyst forecasts. The extent of dispersion is positively related to information uncertainty (e.g., Barron and Stuerke, 1998; Diether *et al.* 2002; Zhang, 2006); thus a greater dispersion implies greater risk.

The fifth proxy of limits to arbitrage is dollar trading volume (*DVOL*), with a higher dollar trading volume indicating more activity in a stock; that is, a higher trading volume implies lower limits to arbitrage (e.g., Lam and Wei, 2011).

3.6 Sample summary statistics

Table 1 presents the sample summary statistics. Panel A reports the means of firm characteristics. Growth firms can be characterized as younger firms with low total assets, while mature firms have larger total assets and a long history. Growth firms are shown generally to have larger bid–ask spreads, greater analyst forecast dispersion and higher idiosyncratic volatility than mature firms, but fewer analysts and lower dollar trading volumes.

[Insert Table 1 about here]

Panel B in Table 1 reports the correlations across the limits-to-arbitrage and investment friction proxies. As idiosyncratic volatility (*IVOL*), bid–ask spread (*BAS*), analyst coverage (*COV*), analyst forecast dispersion (*DISP*) and dollar trading volume

(*DVOL*) all reflect the level of limits to arbitrage, these proxies are highly correlated; for example, dollar trading volume (*DVOL*) has a Pearson (Spearman) correlation of −51.3% (−75.0%) with bid–ask spread (*BAS*) and of 60.7% (77.7%) with analyst coverage (*COV*). Similarly, the firm total assets (*TA*) and firm age (*AGE*) proxies are correlated because both relate to investment frictions: the relevant Pearson and Spearman correlations are 42.0% and 37.0%. Further, the limits-to-arbitrage proxies (*IVOL*, *BAS*, *COV*, *DISP* and *DVOL*) and investment friction proxies (*AGE* and *TA*) are correlated. For Pearson correlations (below the diagonal), firm age (*AGE*) and dollar trading volume (*DVOL*) have a correlation of 27.8%; correlations between firm total assets (*TA*) and idiosyncratic volatility (*IVOL*), bid–ask spread (*BAS*), analyst coverage (*COV*) and dollar trading volume (*DVOL*) are −42.7%, −46.0%, 40.7% and 73.4% respectively. Above the diagonal are the Spearman rank-order correlations and they show a similar but even higher set of correlations in most cases between the proxies of limits to arbitrage and those of investment frictions.

Given the level of these correlations, it is difficult to ascertain whether limits to arbitrage or investment frictions might best explain the asset growth anomaly. Lam and Wei (2011) show that neither explanation dominates; Watanabe *et al.* (2013) argue that due to the high correlation between proxies of limits-to-arbitrage and investment frictions, they not surprisingly produce similar predictions. Our analysis using a growth and mature firm typology seems to capture key cross-sectional variations in the investment friction and limits-to-arbitrage measures. It is therefore important to examine whether or not investors react differently to growth and mature firms after controlling for these factors.

4. Growth type and the asset growth anomaly

Two methodologies are used to examine whether or not growth firms show a stronger asset growth anomaly: sorts of returns according to asset growth, and Fama–MacBeth regressions on the interaction effect of growth type and asset growth[11]. Sorts of returns are used to uncover the basic pattern of comparison of the asset growth effect between growth firms and mature firms. The interaction effect regressions, controlling for limits to arbitrage and investment frictions, are used to demonstrate the unique information contained in growth type.

4.1 Sorting

We first divide firms into two categories – growth and mature – based on the three growth-type proxies: retained earnings scaled by total assets (*RE*), dividends scaled by income (*DIV*) and cash flow scaled by total assets (*CF*). Specifically, we rank firms in deciles based on each of the growth-type proxies; the bottom three deciles are defined as belonging to the growth group, and the top three deciles to the mature group. Following Fama and French (2008) and Lam and Wei (2011), within mature and growth firms we further sort firms into deciles based on asset growth in year t–1 and calculate average monthly returns from July in year t to June in year t+1 for each asset growth decile.

Table 2 reports the monthly raw returns and Fama–French alphas for growth and mature firms for both equal- and value-weighted portfolios. Panel A presents equal-weighted raw returns for each growth-type proxy, showing that future monthly returns decrease as asset growth increases for both growth and mature firms. The differences in returns between low and high asset growth stocks are significantly positive (with t-statistics corrected by the Newey–West (1987) method). These initial results show that both growth and mature firms display the asset growth effect, confirming that this anomaly exists for the US market. Further, the spreads of hedged returns between growth and mature firms

[11] Fama and French (2008) argue that sorts can capture stock return patterns based on an anomaly variable but that they cannot show the marginal effect and the unique information of an anomaly variable. Regression is one solution, of sorts, to this shortcoming.

are reported in the rows 'Spread (G – M)', and are 1.5%, 1.0% and 1.3% respectively for the three growth-type proxies – retained earnings (*RE*), dividends (*DIV*) and cash flow (*CF*). All three spreads are significant at the 1% level and indicate that growth firms have a stronger asset growth anomaly.

When firm size is taken into consideration through value-weighted portfolio construction, Panel B shows further support for the finding that the asset growth anomaly is much stronger in growth firms than in mature firms. Specifically, the asset growth anomaly is not a significant phenomenon in the mature firm, while there is a significant anomaly shown in two out of the three growth-type proxies for growth firms.

A similar conclusion can be drawn when the Fama–French regression alphas are considered in Panels C and D. Overall, the sorting analysis demonstrates that the asset growth anomaly is stronger in growth firms.

[Insert Table 2 about here]

4.2 Regression

The above univariate analyses show a stronger asset growth effect for growth firms. In this subsection we examine the marginal effect of growth type on the asset growth anomaly and whether the growth type holds additional information concerning the asset growth anomaly after controlling for limits to arbitrage and investment frictions. As in Section 4.1, we group firms into deciles based on each of the three growth-type proxies. Then we assign −1 to mature firms, 1 to growth firms and 0 to the rest. We run a Fama–MacBeth regression with an interaction term between growth type and asset growth to capture how growth type affects the slope of asset growth. In each month, we first run the following cross-sectional regression from 1963 to 2011:

$$Ret_i = \alpha + \beta ln(1 + AG)_i + \varphi ln(1 + AG)_i \times GT + \gamma GT + \sum_{j=1}^{3} \theta_j Control_{ij} + \varepsilon, \qquad Eq.\ (1)$$

where *Ret* is the monthly return updated monthly; *AG* is asset growth updated annually; and *GT* indicates growth type, with values assigned as above. Control variables are the natural logarithm of book-to-market ratio (ln*BM*), the natural logarithm of market value (ln*MV*), and the previous 6-month returns (*PRE6RET*), which are widely used predictors of cross-sectional returns.

Table 3 summarizes the regression results. For all three growth-type proxies, the slope of the interaction term between growth type and asset growth is significant and negative. These results support our first hypothesis that the asset growth anomaly is much stronger for growth firms. Interestingly, the non-interactive asset growth coefficient for the *RE* regression is insignificant, which suggests that after controlling for growth type proxied by *RE*, the original asset growth anomaly has disappeared.

[Insert Table 3 about here]

We next examine whether growth type is subsumed by the limits-to-arbitrage and investment friction explanations. As noted in the discussion of correlations in Section 3.6, proxies are correlated within and between the limits-to-arbitrage and investment frictions groups. To address this multicollinearity issue, following Watanabe *et al.* (2013) we control for limits-to-arbitrage and investment friction proxies separately. We run regressions from 1963 to 2011 but for some proxies the regressions start, of necessity, from when the data are available. For example, analyst data are available from 1997; hence we run regressions from 1997 when we control for analyst coverage and analyst forecast dispersion. In each month, we run the following cross-sectional regression:

$$Ret_i = \alpha + \beta \ln(1+AG)_i + \varphi \ln(1+AG)_i \times GT + \gamma GT + \lambda \ln(1+AG)_i \times LIproxi + \kappa LIproxy + \sum_{j=1}^{3} \theta_j Control_{ij} + \varepsilon, \quad \text{Eq. (2)}$$

where *LIproxy* is a proxy of either limits to arbitrage or investment frictions.

Table 4 presents the slope of the interaction between asset growth and growth type. Panels A to C show the results for each of the three growth-type proxies – *RE*, *DIV* and *CF*. In each panel we control for the five limits-to-arbitrage proxies and the two investment friction proxies, giving us 21 regressions in total across the three panels. The results for growth-type proxy *RE* (Panel A) show that six out of seven regressions have significantly negative coefficients for the interaction between growth type and asset growth. This suggests that the results for growth type proxied by *RE* are robust to controls on most of the existing explanations. The results for growth-type proxy *DIV* (Panel B) show similar though weaker findings, with four out of the seven regressions displaying significantly negative coefficients for the interaction between growth type and asset growth. Finally, the results for growth-type proxy *CF* (Panel C) show that its effects are robust to the control of only one limits-to-arbitrage (Model 1) and one investment friction (Model 7) proxy. This is partly as expected, since firms with lower cash flow are likely to have higher investment frictions. On balance, these sets of regression results show that the growth type of a firm does have some additional information in explaining the relationship between asset growth and stock returns after controlling for limits-to-arbitrage and investment frictions.

[Insert Table 4 about here]

5. Asset growth sequence and the asset growth anomaly

5.1 Univariate analysis

The above results show that growth firms have a stronger asset growth anomaly, a finding that gives support to the overreaction explanation. Further, if the asset growth anomaly is indeed driven by overreaction, we would expect the sequence of asset growth to affect the asset growth anomaly. More specifically, we will argue that investors overreact to firm asset growth when they see a growth sequence, and that, as the sequence becomes longer, investors overreact more.

To construct asset growth sequence portfolios we first sort firms into deciles in the June of each year, based on asset growth; the top and bottom two asset growth deciles in each year are defined as the high and low asset growth groups respectively. We then look back to find which asset growth decile the firm is allocated to in the previous year and more. H1 denotes the portfolio, at formation date, of firms in the high asset growth group in June of both year t and the previous year t–1 (but not in that of year t–2). Hi denotes the portfolio of firms remaining in the high asset growth group over the previous i consecutive years (where i = 2, 3, or 4). We repeat this procedure for the low asset growth sequence groups, L1 to L4.

To ascertain whether returns decrease (increase) with a longer high (low) asset growth sequence, we show equal-weighted average monthly returns for each growth sequence portfolio. Further, we examine the slope of the asset growth regression in each portfolio to investigate whether the asset growth anomaly is stronger with an increase in the asset growth sequence.

Panel A in Table 5 shows the return pattern of the growth sequence portfolios. For the high asset growth sequences, the equal-weighted returns reported in the H column are decreasing monotonically from H1 to H4, from 0.86% to 0.36%. The difference between H4 and H1 is significantly negative, indicating that firms with a longer sequence of high asset growth have lower returns in the near future. For the low asset growth sequences, L, the equal-weighted returns do not show a monotonic pattern of returns increasing with a longer asset growth sequence; nevertheless, the significantly positive return difference between L4 and L1 confirms our expectation (for low growth firms, those firms with longer sequence earn higher returns). When we consider the hedged return in each sequence group, the returns of L – H are all positive and significant, which confirms the asset growth effect in all groupings. Furthermore, this hedged return increases monotonically from Sequences 1 to 4 and the difference between the longest and shortest sequence is statistically significant. Economically, investing in the hedged portfolio of the longest growth sequence will have more than double the return (1.73%) of the shortest growth sequence (0.83%). Overall, the evidence is consistent with investors behaving according to the representativeness heuristic; that is, returns diminish with more consecutive years of high asset growth and increase with more consecutive years of low asset growth.

In a further test, we directly analyse whether the asset growth anomaly increases as the asset growth sequence increases by using regression on asset growth. Within each growth sequence portfolio, we employ a Fama–MacBeth regression that controls for the natural logarithm of market value, the natural logarithm of book-to-market ratio, and the previous 6-month returns. The slope coefficients are reported in Panel B of Table 5. For the high asset growth sequences, three out of four coefficients are significantly negative, confirming the asset growth effect. The slope difference between H1 and H4 is -6.76 and significant at the 10% level; suggesting that firms with a longer asset growth sequence show a stronger asset growth anomaly. In contrast, for the low asset growth sequences there is only very weak evidence of the asset growth anomaly, and the slope difference between L1 and L4 is not significant. The asymmetric pattern suggests that the asset growth anomaly is mainly driven by an overreaction to high asset growth. This further confirms that the asset growth anomaly is more likely to be caused by investors' appetite for growth (the high-growth sequence) rather than contraction (the low-growth sequence). The asset growth slope coefficients for portfolios including both high- and low-growth firms in each sequence further support our second hypothesis that the asset growth anomaly is stronger for firms with a longer sequence of asset growth.

[Insert Table 5 about here]

5.2 Multiple regression

In this subsection, we test whether the sequence of asset growth continues to influence the asset growth anomaly after controlling for limits-to-arbitrage and investment friction proxies. We perform Fama–MacBeth regressions of monthly returns on asset growth, interacting with the asset growth sequence, limits-to-arbitrage proxies, investment friction proxies, book-to-market ratio, market value and previous 6-month returns. Given the correlation within and between the limits-to-arbitrage and investment friction proxies, following the procedure in Section 4.2 we include them in separate regressions. In each month, we run the following cross-sectional regression:

$$Ret_i = \alpha + \beta \ln(1 + AG)_i + \varphi_1 \ln(1 + AG)_i \times High\,sequence + \varphi_2 \ln(1 + AG)_i \times Low\,sequence + \gamma_1 High\,sequence + \gamma_2 Low\,sequence + \lambda ln(1 + AG)_i \times LIproxy + \kappa LIproxy + \sum_{j=1}^{3} \theta_j Control_{ij} + \varepsilon ,$$

Eq. (3)

where *Ret* is the monthly return updating monthly; *AG* is asset growth updating annually; *High* (*Low*) *sequence* is the length of the sequence; and *LIproxy* is a proxy from either the limits-to-arbitrage or the investment friction group. Control variables are the natural logarithm of book-to-market ratio (ln*BM*), the natural logarithm of market value (ln*MV*), and the previous 6-month returns (*PRE6RET*) which are widely used predictors of cross-sectional returns.

Table 6 reports the slope of interaction between asset growth sequence and asset growth. Model 1 has no limits-to-arbitrage or investment friction proxies; in Models 2 to 6 we control for limits-to-arbitrage proxies and in Models 7 to 8 for investment friction proxies. The slope of interaction between the high asset growth sequence and asset growth is significantly negative, with Models 2 to 8 showing a significantly negative slope for the interaction term except when controlling for idiosyncratic volatility, analyst forecast dispersion and firm age. To summarize, these results broadly support the prediction that the asset growth anomaly will be stronger when the asset growth sequence is longer. They therefore give weight to the argument that overreaction is the mechanism that drives the asset growth anomaly and representativeness is the heuristic that strengthens the relationship.

[Insert Table 6 about here]

6. Robustness testing and further evidence

6.1 Past growth effect

Cooper *et al.* (2008) show that asset growth can affect future returns beyond the first year. Our analyses, in the previous section, showing a stronger asset growth effect following a longer sequence of high or low growth, could potentially capture any spillover effect of previous growth. To resolve this concern, we rerun our analysis including the previous three periods of asset growth as a control for each asset growth sequence regression. Table 7 reports the results, showing that the asset growth slope coefficients in general increase as growth sequence increases, which is consistent with the findings in Table 5, Panel B. In particular, after controlling for the effect of past asset growth, these results show that investor overreaction increases with the length of growth sequence only after more than one consecutive growth years (from sequence 2 to 4) have been observed. Overall, our findings are thus robust to the control of past growth.

[Insert Table 7 about here]

6.2 Further evidence on overreaction

So far, our test for the overreaction explanation follows the traditional setup by studying the return reversal pattern after growth. If investor overreaction to asset growth is in fact an explanation for the anomaly, evidence of price overreaction to growth information would be expected during the formation period. We study this possibility by running regression analyses of contemporary returns on asset growth and further interactions with growth type and growth sequence.[12] Table 8 reports the regression results from a setup similar to those used to study the asset growth effect as shown in Tables 3 and 7, for growth type and growth sequence respectively. The only difference is that the dependent variable in Table 8 is returns during the formation period rather than subsequent returns.

[Insert Table 8 about here]

Panel A in Table 8 shows the asset growth slope coefficients as significant and positive, that is, opposite in sign to the regressions using future returns as shown in Table 3. This confirms that the subsequent reversal effect is indeed driven by price movement conditional on asset growth during the formation period. Furthermore, supporting our first hypothesis, growth type demonstrates additional explanatory power over investor overreaction to growth. The interaction terms of asset growth and growth-type proxy, for two out of the three (*DIV* and *CF*), are significant and positive, suggesting that investors react more per unit of asset growth in growth firms. Panel B then provides consistent evidence for the growth sequence effect, showing that investors react more per unit of asset growth as the growth sequence increases.

Overall, the findings in Table 8 provide additional confirmation that the asset growth effect is indeed driven by investor overreaction to growth information during the formation period. Although the life-cycle proxies may potentially correlate with the proxies of investment frictions (used for testing the *q*-theory explanation), the evidence of price movement during the formation period confirms that the moderation effect of growth type does in fact capture the variation in investor overreaction to growth. This provides further evidence to differentiate our account from the *q*-theory explanations.

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[12] We thank the referee for suggesting the possibility of providing further evidence of overreaction through studying price movement during the formation period.

7. Conclusion

This paper extends the search for an explanation of the asset growth anomaly. Previous studies find evidence that firms with higher limits-to-arbitrage and high investment frictions show a stronger asset growth anomaly. In the current study, we show that growth firms demonstrate a stronger asset growth anomaly than mature firms and that this result is robust to both sorting and regression methodologies. Furthermore, we show that the firm growth phase provides additional information beyond limits to arbitrage and investment frictions in terms of explaining the asset growth anomaly.

We then show that the way investors react to firm asset growth is consistent with overreaction underpinned by representativeness. When investors see a series of asset growth surprises, they tend to overreact to firm asset growth, and they overreact more when the length of the sequence increases. Hence, the evidence presented here further supports overreaction as the potential source of the asset growth anomaly, based on the representativeness heuristic in relation to asset growth sequence.

In summary, we show that growth firms have a greater tendency to display the asset growth anomaly over and above limits to arbitrage and investment frictions, and that, furthermore, this effect seems to be explained by investor overreaction underpinned by the representativeness heuristic. This evidence complements and extends the initial analysis of the mispricing hypothesis by Cooper *et al.* (2008).

Appendix. Definition of variables

Asset growth (*AG*) is calculated by the equation: $AG_t = TA_{t-1}/TA_{t-2} - 1$.

Control variables

Book-to-market ratio (*BM*) is the book value of assets in year *t*–1 divided by market value at the end of year *t*–1. Book value is total assets minus liabilities, plusbalance sheet deferred taxes and investment tax credits, minus preferred stock liquidation value if available, or redemption value if available, or carrying value if available (e.g., Fama and French, 1993).

Market value (*MV*) is the market capitalization at the end of June in year *t*, measured in millions of dollars. Market capitalization is price multiplied by outstanding shares.

Previous 6-month returns (*PRE6RET*) is the past 6-month compounding returns ending at the end of June in year *t*.

Growth-type proxies

Retained earnings (*RE*) is the retained earnings in the previous fiscal year divided by total assets in the previous fiscal year.

Dividend (*DIV*) is the total dividend, if available, divided by income, before extraordinary items, in the previous fiscal year.

Cash flow (*CF*) is cash flow scaled by total assets in the previous fiscal year. Cash flow is operating income after depreciation minus accruals. Accruals are the change of non-cash current assets minus the change of current liabilities and depreciation.

Limits-to-arbitrage proxies

Idiosyncratic volatility (*IVOL*) is the standard deviation of the residual from the regression of stock return on the market return over the past 12 months ending at the end of June in year *t*. (A 36-month history is required to estimate the regression, or a minimum of 24 months if 36 months of data is not available.)

Bid–ask spread (*BAS*) is the time series average of $2 \times \left| price - \frac{(ask+bid)}{2} \right| / price$ over the past 12 months, ending at the end of June in year *t* (e.g., Lam and Wei, 2011).

Analyst coverage (*COV*) is the number of analysts following the firm at the end of June in each year.

Analyst forecast dispersion (*DISP*) is the standard deviation of analyst forecasts for earnings per share at the end of June in year *t*, scaled by stock price at the end of June in year *t*–1.

Dollar trading volume (*DVOL*) is the time series average of the past 12-month dollar trading volume that is the closing price multiplied by monthly traded shares ending at the end of June in year *t*, measured in millions of dollars. (If there is no 12-month information, a minimum of 6 months of data are required.)

Investment friction proxies

Firm age (*AGE*) is the number of years a stock has appeared in the CRSP database as at the end of June in year *t*.

Firm total assets (*TA*) is the book value of total assets in the previous fiscal year.

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Table 1. Descriptive statistics and correlations

Panel A of this table reports the means of firm characteristics. Firms are sorted into deciles based on the three growth-type proxies – retained earnings scaled by total assets (*RE*), dividends scaled by income before extraordinary items (*DIV*) and cash flow scaled by total assets (*CF*). The top and bottom three deciles are defined as mature and growth firms respectively, for *RE*, *DIV* and *CF*. Differences between growth and mature firms are reported, with *t*-statistics. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. Panel B reports Pearson correlations below the diagonal and Spearman rank-order correlations above the diagonal for limits-to-arbitrage and investment friction proxies. The definitions of these proxies are given in the appendix.

Panel A: Descriptive statistics

	RE				*DIV*				*CF*			
	Growth	Mature	Diff(G–M)	*t*(G–M)	Growth	Mature	Diff(G–M)	*t*(G–M)	Growth	Mature	Diff(G–M)	*t*(G–M)
IVOL	0.21	0.10	0.10***	174.33	0.17	0.09	0.08***	158.06	0.20	0.09	0.11***	187.44
BAS	0.04	0.02	0.02***	73.71	0.03	0.01	0.02***	64.94	0.04	0.01	0.03***	95.09
COV	80.74	100.68	–19.94***	–11.04	68.47	95.47	–27.00***	–11.18	67.51	126.75	–59.24***	–30.27
DISP	105.90	23.09	82.77**	2.53	155.70	34.23	121.43***	2.60	84.46	39.73	44.74	1.48
DVOL	0.48	3.19	–2.71***	–27.83	0.81	3.15	–2.34***	–18.90	0.48	4.94	–4.46***	–38.65
AGE	7.83	14.95	–7.12***	126.28	8.55	15.96	–7.42***	–95.23	7.82	15.42	–7.59***	125.50
TA	287	2109	–1822***	–42.30	920	4519	–3599***	–21.28	188	4423	–4234***	–69.49

Panel B: Correlations

	IVOL	*BAS*	*COV*	*DISP*	*DVOL*	*AGE*	*TA*
IVOL	1	0.479	–0.084	0.190	–0.233	–0.309	–0.513
BAS	0.340	1	–0.725	–0.441	–0.750	–0.302	–0.711
COV	–0.094	–0.326	1	0.633	0.777	0.187	0.521
DISP	0.009	0.011	0.010	1	0.462	0.055	0.296
DVOL	–0.189	–0.513	0.607	0.006	1	0.193	0.730
AGE	–0.243	–0.188	0.199	0.003	0.278	1	0.370
TA	–0.427	–0.460	0.407	0.006	0.734	0.420	1

Table 2. Asset growth effect in growth and mature firms

This table reports the average monthly raw returns and Fama–French alphas (both in %) for each asset growth group over one year for both growth and mature firms. Firms are sorted into deciles based on the three growth-type proxies – retained earnings scaled by total assets (*RE*), dividends scaled by income before extraordinary items (*DIV*) and cash flow scaled by total assets (*CF*); the top and bottom three deciles are defined as mature and growth firms respectively, for *RE*, *DIV* and *CF*. Within mature and growth firms, firms are further sorted into deciles based on asset growth rate; the top (bottom) two deciles are defined as high (low) asset growth. For each asset growth decile, stocks are held for one year from July in year t to June in year t+1. The table reports average returns or alphas over the period, and the spread is the difference between the low and high asset growth groups. The table also reports the average of the hedged difference between growth and mature firms for each growth-type proxy; hedged returns are calculated as the return of the low asset growth group minus that of the high asset growth group. Panel A reports equal-weighted portfolio average monthly raw returns. Panel B reports value-weighted portfolio average monthly raw returns. Panel C reports equal-weighted portfolio Fama–French monthly alphas. Panel D reports value-weighted portfolio Fama–French monthly alphas. The sample period is from 1963 to 2011. t-values are based on Newey–West (1987) standard errors, correcting for heteroscedasticity and autocorrelation. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Table 2. Continued

Panel A: Equal-weighted portfolio average monthly raw returns

Proxy	Growth type	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Diff (1–10)	*t*	Firm–year obs
RE	Mature	1.6	1.5	1.4	1.4	1.3	1.4	1.4	1.3	1.1	1.0	0.6***	3.89	59855
	Growth	2.1	2.0	1.8	1.8	1.5	1.4	1.2	0.7	0.7	0.0	2.0***	7.69	59852
	Spread (G–M)											1.5***	5.78	
DIV	Mature	1.5	1.4	1.4	1.2	1.3	1.2	1.2	1.1	1.0	0.9	0.7***	5.06	25272
	Growth	1.8	1.6	1.7	1.4	1.4	1.3	1.4	1.1	1.0	0.8	1.0***	5.82	25267
	Spread (G–M)											1.0***	3.06	
CF	Mature	1.6	1.4	1.4	1.4	1.2	1.2	1.2	1.2	1.1	0.8	0.8***	4.94	57967
	Growth	2.1	2.0	2.0	1.6	1.4	1.3	1.0	0.6	0.4	–0.1	2.1***	7.95	57963
	Spread (G–M)											1.3***	5.11	

Panel B: Value-weighted portfolio average monthly raw returns

Proxy	Growth type	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Diff (1–10)	*t*
RE	Mature	1.8	1.7	1.4	1.4	1.4	1.3	1.5	1.5	1.6	1.8	–0.1	–0.27
	Growth	4.3	3.5	3.4	2.9	2.0	2.3	2.4	2.3	2.5	2.5	1.9***	5.01
	Spread (G–M)											1.9***	5.13
DIV	Mature	1.6	1.5	1.4	1.3	1.2	1.2	1.2	1.1	1.3	1.2	0.3	1.51
	Growth	2.3	1.7	1.8	1.6	1.9	1.6	1.9	1.7	1.6	1.9	0.4	1.56
	Spread (G–M)											0.1	0.39
CF	Mature	1.9	1.7	1.4	1.4	1.3	1.3	1.5	1.5	1.5	1.6	0.3	1.55
	Growth	4.2	3.8	3.7	3.1	2.8	2.8	2.9	2.5	2.6	2.5	1.7***	4.22
	Spread (G–M)											1.3***	3.40

Table 2. Continued

Panel C: Equal-weighted portfolio Fama–French monthly alphas

Proxy	Growth type	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Diff (1–10)	*t*
RE	Mature	0.7	0.5	0.6	0.7	0.5	0.6	0.5	0.5	0.3	0.3	0.4**	2.11
	Growth	0.7	0.4	0.5	0.5	0.3	0.2	0.0	–0.6	–0.4	–1.1	1.8***	5.74
	Spread (G–M)											1.4***	4.03
DIV	Mature	0.4	0.5	0.5	0.3	0.5	0.4	0.3	0.3	0.3	–0.1	0.5***	3.04
	Growth	0.8	0.6	0.8	0.3	0.5	0.3	0.4	0.2	0.0	–0.4	1.1***	5.66
	Spread (G–M)											0.6**	2.47
CF	Mature	0.5	0.5	0.6	0.5	0.4	0.5	0.5	0.4	0.4	0.0	0.5***	2.81
	Growth	0.5	0.7	0.6	0.4	0.4	0.2	0.0	–0.5	–0.6	–1.0	1.6***	4.67
	Spread (G–M)											1.1***	3.86

Panel D: Value-weighted portfolio Fama–French monthly alphas

Proxy	Growth type	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Diff (1–10)	*t*
RE	Mature	1.0	0.9	0.8	0.7	0.8	0.8	0.8	0.9	0.9	1.2	–0.2	–0.77
	Growth	3.0	2.3	2.2	1.9	1.3	1.6	1.4	1.4	1.4	1.4	1.6***	3.45
	Spread (G–M)											1.8***	3.71
DIV	Mature	0.8	0.9	0.6	0.6	0.6	0.5	0.5	0.5	1.0	0.5	0.3	1.12
	Growth	1.4	1.1	1.2	1.0	1.4	0.7	1.2	1.0	1.0	0.9	0.5*	1.88
	Spread (G–M)											0.2	0.60
CF	Mature	1.0	1.0	0.8	0.7	0.7	0.7	0.9	0.8	0.8	0.9	0.1	0.43
	Growth	2.9	2.9	2.6	2.1	1.8	1.9	2.1	1.6	1.5	1.6	1.2***	2.91
	Spread (G–M)											1.2***	2.86

Table 3. Growth type and the asset growth anomaly

This table reports the time-series average of the estimated coefficients of monthly regressions from 1963 to 2011. In each month we run the following regression:

$$Ret_i = \alpha + \beta ln(1 + AG)_i + \varphi ln(1 + AG)_i \times GT + \gamma GT + \sum_{j=1}^{3} \theta_j Control_{ij} + \varepsilon, \qquad \textit{Eq. (1)}$$

where Ret_i is the monthly raw return; *AG* is firm asset growth; *GT* indicates firm growth type (1 for growth, -1 for mature and 0 for the rest). Firms are sorted into deciles based on the three growth-type proxies – retained earnings scaled by total assets (*RE*), dividends scaled by income before extraordinary items (DIV) and cash flow scaled by total assets (*CF*); the top and bottom three deciles are defined as mature and growth firms respectively, for *RE*, *DIV* and *CF*. Control variables are the natural logarithm of book-to-market ratio (ln*BM*), the natural logarithm of market value (ln*MV*), and the previous 6-month returns at the end of June (*PRE6RET*). *t*-values in parentheses are based on Newey–West (1987) standard errors, correcting for heteroscedasticity and autocorrelation. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

	RE	*DIV*	*CF*
Intercept	2.07***	1.60***	2.49***
	(6.80)	(6.30)	(7.47)
ln(1+*AG*)	–0.21	–0.66***	–0.59***
	(–0.78)	(–2.79)	(–2.98)
ln(1+*AG*)**GT*	–1.12***	–0.78**	–0.94***
	(–3.53)	(–2.52)	(–3.46)
GT	–0.07	0.23**	–0.34**
	(–0.49)	(2.33)	(–2.16)
ln*BM*	0.18***	0.07*	0.08**
	(3.90)	(1.82)	(1.97)
ln*MV*	–0.14***	–0.09***	–0.19***
	(–3.79)	(–2.74)	(–5.47)
PRE6RET	0.16	0.63***	0.26
	(0.87)	(3.11)	(1.50)

Table 4. Growth type, limits-to-arbitrage, investment frictions and the asset growth anomaly

This table reports the time-series average of the estimated coefficients of monthly regressions from 1963 to 2011. In each month we run the following regression:

$$Ret_i = \alpha + \beta \ln(1 + AG)_i + \varphi \ln(1 + AG)_i \times GT + \gamma GT + \lambda \ln(1 + AG)_i \times LIproxy + \kappa LIproxy + \sum_{j=1}^{3} \theta_j Control_{ij} + \varepsilon,$$

Eq. (2)

where Ret_i is the monthly raw return; *AG* is firm asset growth; *GT* indicates firm growth type (1 for growth, -1 for mature and o for the rest); *LIproxy* is a proxy of either limits to arbitrage or investment frictions. Firms are sorted into deciles based on the three growth-type proxies – retained earnings scaled by total assets (*RE*), dividends scaled by income before extraordinary items (*DIV*) and cash flow scaled by total assets (*CF*), shown in Panels A, B and C respectively; the top and bottom three deciles are defined as mature and growth firms respectively for *RE, DIV* and *CF*. Models 1 to 5 report the interaction effect of growth type and asset growth by controlling for the five limits-to-arbitrage proxies – respectively idiosyncratic volatility (*IVOL*), bid–ask spread (*BAS*), analyst coverage (*COV*), analyst forecast dispersion (*DISP*) and dollar trading volume (*DVOL*). Models 6 and 7 report the interaction effect of growth type and asset growth by controlling for the two investment friction proxies – respectively firm age (*AGE*) and firm total assets (*TA*). Control variables are the natural logarithm of book-to-market ratio (ln*BM*), the natural logarithm of market value (ln*MV*), and the previous 6-month returns at the end of June (*PRE6RET*). *t*-values in parentheses are based on Newey–West (1987) standard errors, correcting for heteroscedasticity and autocorrelation. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Table 4. Continued

Panel A: Growth-type proxy *RE*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	1.95***	1.01**	2.20***	2.15***	1.54*	2.07***	2.10***
	(8.70)	(2.33)	(5.08)	(5.40)	(1.89)	(5.80)	(6.58)
ln(1+*AG*)	0.32	–0.20	–0.86**	0.05	0.15	–0.54	–1.38**
	(0.83)	(–0.50)	(–2.57)	(0.16)	(0.32)	(–0.91)	(–2.30)
ln(1+*AG*)**GT*	–0.63*	–1.34***	–0.80	–1.14**	–0.79**	–1.00***	–0.73**
	(–1.69)	(–2.86)	(–1.47)	(–2.05)	(–2.40)	(–2.95)	(–2.22)
ln(1+*AG*)**IVOL*	–5.20						
	(–1.56)						
ln(1+*AG*)**BAS*		10.45					
		(–0.82)					
ln(1+*AG*)**COV*			0.02				
			(1.04)				
ln(1+*AG*)**DISP*				–10.25			
				(–0.91)			
ln(1+*AG*)**DVOL*					0.14		
					(1.43)		
ln(1+*AG*)**AGE*						0.01	
						(0.07)	
ln(1+*AG*)**TA*							0.23**
							(2.15)
GT	–0.13	–0.07	0.00	0.12	–0.08	–0.09	–0.13
	(–1.10)	(–0.30)	(0.01)	–0.53	(–0.58)	(–0.60)	(–0.83)
IVOL	1.61						
	(1.07)						
BAS		8.09					
		(1.30)					
COV			0.00				
			(0.58)				
DISP				–5.07**			
				(–2.35)			
DVOL					–0.06		
					(–0.80)		
AGE						0.01	
						(0.16)	
TA							0.09
							(1.11)
ln*BM*	0.17***	0.20***	0.12*	0.16**	0.18***	0.17***	0.08
	(4.04)	(2.74)	(1.80)	(2.32)	(4.26)	(3.99)	(1.19)
ln*MV*	–0.13***	0.04	–0.15***	–0.12***	–0.07	–0.14***	–0.24***
	(–4.15)	(0.78)	(–2.69)	(–2.71)	(–0.82)	(–3.80)	(–3.08)
PRE6RET	0.10	0.08	0.09	0.06	0.27	0.16	0.22
	(0.59)	(0.46)	(0.50)	(0.33)	(1.60)	(0.90)	(1.20)

Table 4. Continued

Panel B: Growth-type proxy *DIV*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	1.48***	1.25***	1.65***	1.57***	0.97	1.52***	1.70***
	(7.66)	(3.23)	(4.39)	(4.61)	(1.35)	(5.32)	(6.60)
ln(1+*AG*)	0.07	0.04	–0.46	0.00	0.32	–1.25*	–1.91***
	(0.18)	(0.08)	(–1.27)	(0.01)	(0.84)	(–1.68)	(–3.35)
ln(1+*AG*)**GT*	–0.31	–1.07*	–0.45	–0.66	–1.01***	–0.63**	–0.79**
	(–0.88)	(–1.95)	(–0.99)	(–1.34)	(–3.26)	(–2.00)	(–2.54)
ln(1+*AG*)**IVOL*	–10.10**						
	(–2.00)						
ln(1+*AG*)**BAS*		–48.72					
		(–1.61)					
ln(1+*AG*)**COV*			–0.00				
			(–0.24)				
ln(1+*AG*)**DISP*				–12.26			
				(–1.25)			
ln(1+*AG*)**DVOL*					0.24***		
					(2.76)		
ln(1+*AG*)**AGE*						0.05	
						(0.28)	
ln(1+*AG*)**TA*							0.24**
							(2.57)
GT	0.18**	0.32**	0.30***	0.35***	0.27***	0.22**	0.24**
	(2.07)	(2.39)	(2.70)	(3.02)	(3.07)	(2.24)	(2.47)
IVOL	1.55						
	(0.85)						
BAS		2.00					
		(0.23)					
COV			0.00				
			(0.75)				
DISP				–1.62			
				(–0.97)			
DVOL					–0.08		
					(–1.30)		
AGE						0.02	
						(0.72)	
TA							–0.01
							(–0.22)
ln*BM*	0.06*	0.00	0.02	0.09*	0.08**	0.06	0.04
	(1.78)	(0.01)	(0.39)	(1.65)	(2.08)	(1.60)	(0.79)
ln*MV*	–0.08***	–0.05	–0.09*	–0.07*	–0.01	–0.10***	–0.09
	(–2.91)	(–0.92)	(–1.86)	(–1.74)	(–0.16)	(–3.12)	(–1.37)
PRE6RET	0.64***	0.79***	0.53**	0.48**	0.69***	0.64***	0.63***
	(3.27)	(3.18)	(2.38)	(2.05)	(3.48)	(3.12)	(3.09)

Table 4. Continued

Panel C: Growth-type proxy *CF*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	2.43***	1.78***	2.34***	2.26***	1.77**	2.33***	2.66***
	(9.34)	(3.39)	(4.76)	(5.10)	(2.16)	(6.44)	(7.93)
ln(1+*AG*)	–0.42	–0.62*	–0.69**	–0.22	–0.25	–0.80	–2.43***
	(–1.29)	(–1.76)	(–2.40)	(–0.79)	(–0.82)	(–1.48)	(–3.49)
ln(1+*AG*)**GT*	–0.80***	–0.70	–0.29	–0.41	0.01	–0.83***	–0.02
	(–2.59)	(–1.50)	(–0.71)	(–0.88)	(0.04)	(–2.93)	(–0.05)
ln(1+*AG*)**IVOL*	–2.10						
	(–0.71)						
ln(1+*AG*)**BAS*		–7.78					
		(–0.38)					
ln(1+*AG*)**COV*			0.01				
			(0.62)				
ln(1+*AG*)**DISP*				–19.26**			
				(–2.04)			
ln(1+*AG*)**DVOL*					0.27***		
					(2.94)		
ln(1+*AG*)**AGE*						–0.04	
						(–0.39)	
ln(1+*AG*)**TA*							0.29***
							(2.69)
GT	–0.37***	–0.71***	–0.44**	–0.37*	–0.42***	–0.33**	–0.43***
	(–2.77)	(–2.93)	(–2.20)	(–1.72)	(–2.90)	(–2.16)	(–2.82)
IVOL	0.58						
	(0.42)						
BAS		13.46*					
		(1.95)					
COV			0.00				
			(0.79)				
DISP				–2.44			
				(–1.29)			
DVOL					–0.10		
					(–1.27)		
AGE						0.06	
						(1.33)	
TA							–0.05
							(–0.76)
ln*BM*	0.08**	0.03	0.04	0.05	0.07*	0.08*	0.10*
	(2.14)	(0.51)	(0.69)	(0.90)	(1.84)	(1.86)	(1.68)
ln*MV*	–0.19***	–0.09	–0.17***	–0.14***	–0.11	–0.19***	–0.17**
	(–6.05)	(–1.39)	(–2.95)	(–3.13)	(–1.24)	(–5.55)	(–2.35)
PRE6RET	0.21	0.11	0.36*	0.35*	0.32*	0.26	0.24
	(1.21)	(0.56)	(1.77)	(1.67)	(1.88)	(1.48)	(1.44)

Table 5. Returns and the asset growth anomaly for growth sequence portfolios

This table presents the average monthly raw returns (in %) and asset growth slopes for different asset growth sequences. To form the sequence groups, firms are sorted into deciles based on asset growth rate; the top (bottom) two deciles in each year are defined as high (low) asset growth. Firm asset growth is then traced back to identify the length of high- (low-) growth sequence at year end t. Firms in a high (low) decile in year t and also in year t–1, but not in year t–2, are placed in the H1 (L1) group; the H2 (L2), H3 (L3) and H4 (L4) groups are similarly constructed according to sequence length. Panel A reports the average monthly return in the 12 months after the formation period. Panel B reports the asset growth slope coefficients from the regression of monthly returns on asset growth, the natural logarithm of book-to-market ratio, the natural logarithm of market value, and the previous 6-month returns at the end of June. The regressions are performed on portfolios including stocks in high (H), low (L) and both H and L sequence groups. t-values are based on Newey–West (1987) standard errors, correcting for heteroscedasticity and autocorrelation. Diff(4 – 1) reports the test for the difference between the statistics in Sequences 4 and 1. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Panel A: Hedged returns

Sequence	H	L	Diff (L–H)
1	0.86	1.70	0.83***
2	0.73	2.01	1.28***
3	0.36	1.78	1.42***
4	0.36	2.09	1.73***
Diff (4–1)	–0.50***	0.38**	0.90***

Panel B: Asset growth slopes

Sequence	H	L	H&L
1	–1.18***	0.23	–1.06***
2	–0.77	–2.02*	–1.00***
3	–3.65**	–0.96	–1.55***
4	–7.94*	–1.61	–2.37***
Diff (4–1)	–6.76*	–1.83	–1.31*

Table 6. Growth sequence, limits-to-arbitrage and investment frictions

This table reports the time-series average of the estimated coefficients of monthly regressions from 1963 to 2011. In each month we run the following regression:

$$Ret_i = \alpha + \beta \ln(1 + AG)_i + \varphi_1 \ln(1 + AG)_i \times High\, sequence + \varphi_2 \ln(1 + AG)_i \times Low\, sequence + \gamma_1 High\, sequence + \gamma_2 Low\, sequence + \lambda ln(1 + AG)_i \times LIproxy + \kappa LIproxy + \sum_{j=1}^{3} \theta_j Control_{ij} + \varepsilon,$$

Eq. (3)

where Ret_i is the monthly raw return; *AG* is firm asset growth; *High* (*Low*) *sequence* indicates the length of a high (low) asset growth sequence; *LIproxy* is a proxy of either limits to arbitrage or investment frictions. Models 2 to 6 report the interaction effect of growth type and asset growth by controlling for the five limits-to-arbitrage proxies – respectively idiosyncratic volatility (*IVOL*), bid–ask spread (*BAS*), analyst coverage (*COV*), analyst forecast dispersion (*DISP*) and dollar trading volume (*DVOL*). Models 7 and 8 report the interaction effect of growth type and asset growth by controlling for the two investment friction proxies – respectively firm age (*AGE*) and firm total assets (*TA*). Control variables are the natural logarithm of book-to-market ratio (ln*BM*), the natural logarithm of market value (ln*MV*), and the previous 6-month returns at the end of June (*PRE6RET*). *t*-values in parentheses are based on Newey–West (1987) standard errors, correcting for heteroscedasticity and autocorrelation. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Table 6. Continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	1.85***	1.76***	1.42***	2.05***	1.94***	1.85***	1.98***	1.94***
	(5.02)	(6.93)	(3.38)	(4.27)	(4.53)	(4.68)	(4.73)	(5.17)
ln(1+*AG*)	–0.79***	0.07	–0.66**	–0.67**	0.14	–0.38	–2.50***	–2.07***
	(–3.79)	(0.24)	(–2.00)	(–2.31)	(0.42)	(–1.13)	(–4.24)	(–4.77)
ln(1+*AG*)**High*	–0.25**	–0.17	–0.30**	–0.25*	–0.21	–0.33***	–0.18	–0.26**
	(–2.22)	(–1.50)	(–1.99)	(–1.84)	(–1.46)	(–3.04)	(–1.58)	(–2.32)
ln(1+*AG*)**Low*	–0.29	–0.08	0.56	–0.35	–1.05	–0.35	–0.20	–0.08
	(–1.00)	(–0.29)	(1.27)	(–0.68)	(–1.06)	(–1.20)	(–0.71)	(–0.27)
ln(1+*AG*)**IVOL*		–6.83***						
		(–2.96)						
ln(1+*AG*)**BAS*			–10.12					
			(–1.07)					
ln(1+*AG*)**COV*				0.02*				
				(1.70)				
ln(1+*AG*)**DISP*					–28.93***			
					(–3.12)			
ln(1+*AG*)**DVOL*						0.11		
						(1.64)		
ln(1+*AG*)**AGE*							0.20***	
							(2.63)	
ln(1+*AG*)**TA*								0.26***
								(3.44)
High sequence	–0.07	–0.10*	–0.03	–0.07	–0.08	–0.08	–0.09	–0.07
	(–1.18)	(–1.94)	(–0.28)	(–1.22)	(–1.28)	(–1.34)	(–1.51)	(–1.12)
Low sequence	0.04	0.06	0.07	0.05	0.09	0.05	0.04	0.06
	(0.72)	(1.14)	(0.74)	(0.79)	(1.29)	(0.86)	(0.82)	(1.18)
IVOL		0.39						
		(0.26)						
BAS			3.92					
			(0.86)					
COV				0.00				
				(0.39)				
DISP					–0.77			
					(–0.53)			
DVOL						–0.29**		
						(–2.08)		
AGE							–0.01	
							(–0.86)	
TA								–0.01
								(–0.20)
ln*BM*	0.15***	0.15***	0.13**	0.07	0.09	0.16***	0.15***	0.13**
	(3.10)	(3.46)	(2.00)	(1.27)	(1.54)	(3.41)	(3.17)	(2.32)
ln*MV*	–0.09**	–0.09***	–0.03	–0.13**	–0.10**	–0.09**	–0.09**	–0.10
	(–2.41)	(–2.92)	(–0.72)	(–2.22)	(–2.31)	(–2.00)	(–2.37)	(–1.21)
PRE6RET	0.09	0.08	–0.08	0.20	0.22	0.10	0.09	0.09
	(0.62)	(0.56)	(–0.56)	(1.15)	(1.18)	(0.66)	(0.61)	(0.58)

Table 7. Asset growth effect by growth sequence with control of past growth

This table reports the asset growth effect regression by asset growth sequence with additional control of past growth. Asset growth slopes are from the regression of monthly returns on current and three lags of asset growth, the natural logarithm of book-to-market ratio (ln*BM*), the natural logarithm of market value (ln*MV*), and the previous 6-month returns at the end of June (*PRE6RET*). The regressions are performed on portfolios including stocks in both High and Low (H and L) sequence groups. To form the sequence groups, firms are sorted into deciles based on asset growth rate; the top (bottom) two deciles in each year are defined as high (low) asset growth. Firm asset growth is then traced back to identify the length of high- (low-) growth sequence at year end *t*. Firms in a high (low) decile in year *t* and also in year *t*–1, but not in year *t*–2, are placed in the H1 (L1) group; the H2 (L2), H3 (L3) and H4 (L4) groups are similarly constructed according to sequence length. *t*-values are based on Newey–West (1987) standard errors, correcting for heteroscedasticity and autocorrelation. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

	Sequence = 4		Sequence = 3		Sequence = 2		Sequence = 1	
	Slope	*t*	Slope	*t*	Slope	*t*	Slope	*t*
Intercept	2.85***	3.58	2.42***	4.41	2.00***	4.60	1.95***	4.39
ln(1+*AG*)	–1.74*	–1.92	–1.63**	–2.38	–0.87***	–5.01	–0.93***	–4.91
ln(1+*AG*)_lag1	1.87	1.37	0.36	0.54	–0.48***	–2.89	–0.59*	–1.66
ln(1+*AG*)_lag2	–2.09	–1.00	–0.05	–0.08	0.03	0.13	0.13	0.50
ln(1+*AG*)_lag3	–1.16	–0.73	1.39**	2.20	–0.13	–0.67	–0.50**	–2.05
ln*BM*	0.19	0.78	0.26*	1.77	0.11*	1.72	0.08	1.08
ln*MV*	–0.28**	–2.06	–0.20**	–2.25	–0.09**	–2.10	–0.09*	–1.89
PRE6RET	–0.66	–1.16	–0.17	–0.39	0.10	0.54	0.08	0.39

Table 8. Asset growth and the contemporary return relationship

This table reports the time-series average of the estimated coefficients of monthly regressions from 1963 to 2011. The dependent variable is the monthly raw return between *t*–18 and *t*–6, where *t* is the asset growth formation month (every June). *AG* is firm asset growth. Control variables are the natural logarithm of book-to-market ratio (ln*BM*), the natural logarithm of market value (ln*MV*), and the previous 6-month returns at the end of June (*PRE6RET*). Panel A reports the regression with growth type, where *GT* indicates firm growth type (1 for growth, -1 for mature and 0 for the rest). Firm growth-type classification is as described in Table 2. Panel B reports the regression with growth sequence and additional control of past growth up to three lags. Growth sequence portfolio formation is as described in Table 5. *t*-values are based on Newey–West (1987) standard errors, correcting for heteroscedasticity and autocorrelation. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Panel A: Growth type effect

	RE	*DIV*	*CF*
Intercept	1.34***	0.86***	1.33***
	(4.63)	(3.56)	(4.05)
ln(1+*AG*)	3.30***	0.80***	1.89***
	(11.51)	(3.47)	(7.88)
ln(1+*AG*)**GT*	–0.33	1.62***	1.17***
	(–0.94)	(4.73)	(3.85)
GT	–0.53***	0.97***	–0.64***
	(–3.18)	(8.41)	(–4.27)
ln*BM*	–1.07***	–0.61***	–0.91***
	(–20.68)	(–16.44)	(–19.46)
ln*MV*	–0.13***	–0.05*	–0.09***
	(–3.70)	(–1.79)	(–2.60)
PRE6RET	1.45***	1.45***	1.44***
	(7.05)	(6.33)	(6.84)

Panel B: Growth sequence effect

	Sequence = 4		Sequence = 3		Sequence = 2		Sequence = 1	
	Slope	*t*	Slope	*t*	Slope	*t*	Slope	*t*
Intercept	3.35***	2.96	1.89***	3.41	1.18***	2.77	1.03**	2.29
ln(1+*AG*)	4.44*	1.88	3.39***	6.10	2.78***	13.48	2.74***	13.68
ln(1+*AG*)_lag1	–1.71	–0.92	–2.55***	–4.10	–1.97***	–10.05	–2.23***	–8.57
ln(1+*AG*)_lag2	–1.58	–0.65	–1.45**	–2.25	–1.54***	–6.68	–1.48***	–6.43
ln(1+*AG*)_lag3	–2.13	–0.69	–0.01	–0.02	–0.34*	–1.82	–0.37**	–2.00
ln*BM*	–0.79	–1.17	–1.35***	–7.82	–1.20***	–16.05	–1.37***	–15.82
ln*MV*	–0.30*	–1.68	–0.11	–1.37	–0.01	–0.24	0.00	0.02
PRE6RET	0.97	0.44	0.99**	2.35	1.23***	6.61	1.20***	5.80